Journal of Korea TAPPI
Vol.36.No.5, 2004
Printed in Korea

Model Algorithmic Control for Paper Mills Using Neural Networks

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(Received on August 5, 2004: Accepted on October 29, 2004)

ABSTRACT

In this work the Model Algorithmic Control (MAC) method is applied to control the grade change operations in paper mills. The neural network model for the grade change operations is identified first and the impulse model is extracted from the neural network model. Results of simulations for MAC control of grade change operations are compared with plant operation data. The major contribution of the present work is the application of MAC in the industrial plants based on the identification of neural network models. We can confirm that the proposed MAC method exhibits faster responses and less oscillatory behavior compared to the plant operation data in the grade change operations.

Keywords: grade change operation, Model Algorithmic Control, impulse model, paper mill

1. Introduction

The task of most control systems implemented in the paper mills is to keep the process variables at a steady-state during the production of a single grade. However, during grade change operations, conventional control systems can hardly meet the performance criteria. For this reason most of the grade change operations are executed manually by skilled operators. Improvement of process performance during grade change operations is a challenging problem. Fast grade changes and highly skilled operators may be the only solution to this problem. Because of the lack of proper control tools to make the task of the operators easier, the process performance during grade change operations has not been satisfactory.

The model predictive control methods have found successful applications especially in the area of petrochemical industry. There have been many efforts to employ the model predictive control method in the operation of paper mills. But, because of the complexity and high nonlinearity of the paper mills, an

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appropriate explicit plant model for the paper mill to be used in model predictive control schemes was hardly able to be identified. In this case, a model based on artificial neural networks can be an excellent candidate. Many researchers tried to find out neural network models for paper production processes. The tensile strength of the paper web was identified by using neural networks (1). Wang proposed combination of the model predictive control method with the neural networks to control the cross directional profile of the basis weight (2). Application of the general predictive control method to control the bone dry weight and the ash content of paper has been reported (3).

The key controlled variables in the grade change operations are the basis weight, the ash content and the moisture content of the paper being produced. As the manipulated variables it is common practice to choose the flow rate of the thick stock, the filler flow, the machine speed and the steam pressure. It is desired to control all the three controlled variables simultaneously, but most of the control methods proposed so far have concentrated in the control of only one or two key variables. The PID control method presented by Tang and Shi focused on the basis weight (4). A transition control scheme based on the process model was proposed by some researchers (5-6). The method tries to manipulate the steam pressure to make the moisture content follow the predetermined trajectory.

In the present study the Model Algorithmic Control (MAC) method is proposed to control the grade change operations in paper production plants. As the first step a neural network model for grade change operations is identified. In the actual plant operation, it is impossible to perform step or impulse tests. If the neural model could serve as the "actual" plant, we may be able to get step or impulse model very easily. From the numerical simulations the neural model identified showed excellent agreement with the plant data, which justifies the use of the neural model as the "actual" plant. A multivariable MAC scheme is proposed next to control all the key controlled variables (basis weight, the ash content and the moisture content) simultaneously followed by numerical simulations.

2. Grade change operations

A modern paper machine can be considered as a production line consisting of a stock preparation system, wire section, wet pressing, drying and coating units as shown in Fig. 1. In stock preparation, different raw materials such as chemical pulp from pulp mills, mechanical pulp from chip refiners, chemicals and additives are mixed together. Pulps are usually refined in order to achieve the required product quality. After it is cleaned and diluted, pulp stock is fed into the white-water system in the wire section of the paper machine.

The white-water system consists of the headbox, wire and the circulated white-water that is a filtrate from the wire. White-water is used to dilute the stock to the desired consistency (0.3~1 %) for the paper web forming process. The headbox spreads the stock flow on the wire across the width of the machine and the paper web is formed. After that, water is removed first by wet pressing and then contact drying on steam-heated cylinders. Often, modern paper machines have on-machine coaters that apply pigment coating color on the paper. Coating may be on both sides and even double or triple layered. In addition to these principal systems, there are several support systems such as for broke handling, chemical preparation and so on.

A grade change is a product quality change on a paper machine. In a big grade change, several inputs to the paper machine are changed, for example proportioning of raw materials, refiner loads, stock flows, headbox settings, machine speed, lineal pressures in wet pressing, steam pressures and coating settings. So far the most common way to execute a grade change is by ramping. An open-loop method such as ramping suits grade change well because there are no exact target values for the basis weight and moisture. It is satisfactory if the target values hit inside an acceptance range after the grade change. Most grade changes are basis weight transitions. The basis weights in a production schedule are run in a cycle. The cycle is optimized so that the basis weight changes are as small as possible. The ideal condition is that the allowed ranges of sequential grades overlap.

A typical grade change consists of a calculation of target values and a dynamic co-ordination of paper machine speed, pulp stock flow and steam. It is crucial to a successful grade change that the new target values are accurately known. Stock flow and machine speed together control both the production rate and basis weight. Drying is controlled by steam pressure but often, only the last steam groups are used for control purpose. Because of long time constants and dead times in the drying process, the target values for steam pressures are the most important. Also raw material properties, the condition of the paper machine, basis weight, moisture and speed, all affect the drying rate. The machine tender usually gets the initial target values from the records of the previous runs.

3. Neural Network Model

Artificial neural networks are well known and widely used in modeling and control area. In the present study a multilayer perceptron network with backpropagation algorithm was

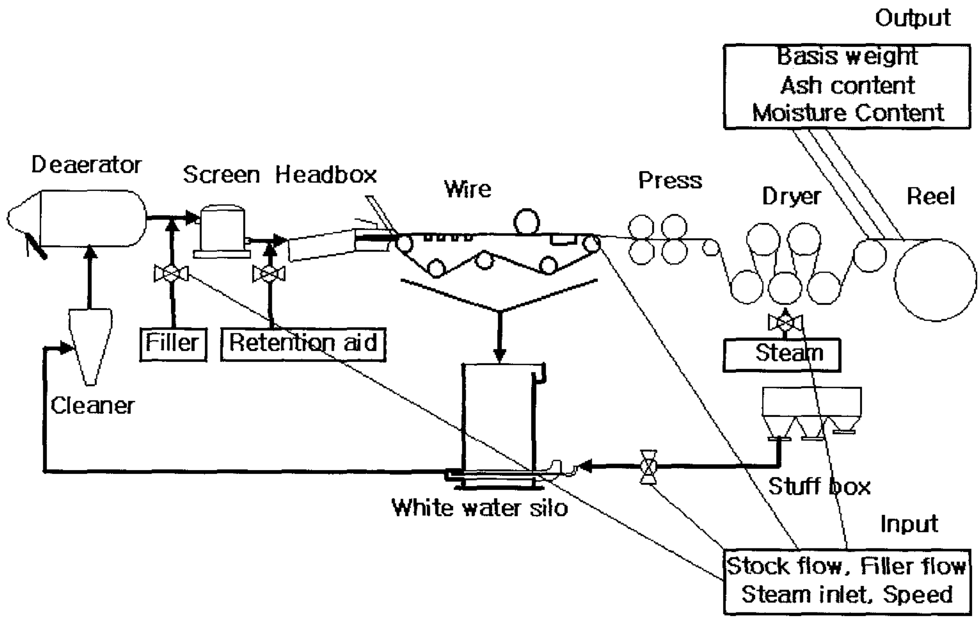

Fig. 1. Schematics of paper machine.

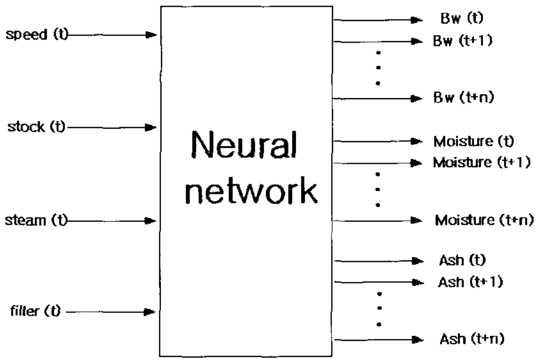

Fig. 2. Neural network structure for impulse model.

constructed. Learning was performed so that outputs track targets within permitted error range given operational inputs.

The primary purpose of learning in this work is to extract the impulse model to be used in control. As can be seen in Fig. 2, impulse change is introduced at the present time t and outputs obtained for next n time steps are used as impulse model parameters. Levenberg-Marquardt learning algorithm was employed and bipolar sigmoid (Eq.[1]) was used as the active transfer function.

$$f(net) = \frac{2}{1+e^{-\lambda \times net}} - 1 \qquad [1]$$

$f(net)$: activation function

net : activation value of neuron.

There are 4 and 3 neurons in the input and output layers respectively. The hidden layer contains 25 neurons. Plant operation data were collected for more than 15 different grades of papers. Part of the operation data was used as training set and theremaining data set was employed in the validation of the neural model. Figs. 3 and 4 show the results of validations of the neural network model for the paper company A and B respectively. Among the three output variables, the basis weight (BW) is by far the most important and major effort is taken to control BW first in the plant operation. As we can see in Figs. 3 and 4, results of the numerical validation simulations show excellent agreement with plant operation data. This justifies the use of the neural network model as the "actual" plant in the model predictive control scheme.

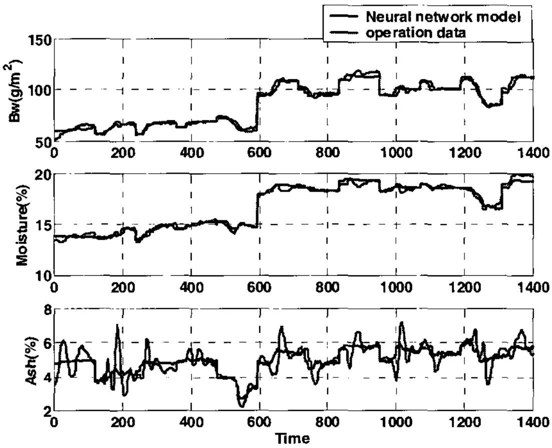

Fig. 3. Validation of the neural model (Company A).

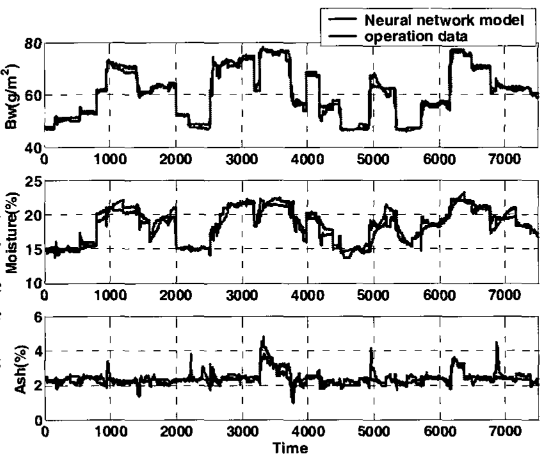

Fig. 4. Validation of the neural model (Company B).

4. Model Algorithmic Control (MAC) Method

Model predictive control (MPC) is a basic concept or idea that can be implemented in many ways, depending on models used and assumptions made. The exact models for the paper manufacturing processes can be found elsewhere (6-7). The finite step and impulse models limit applications to open-loop stable processes and require many model coefficients to describe the response. It is now recognized that there are many advantages to using discrete state space models. State space models require fewer model parameters than step and impulse response models to describe process behavior. The step and impulse response models are all linear. For some processes where the process operating conditions are changed frequently, a single linear model may not describe the dynamic behavior of the process over the wide range of conditions. For the paper production processes, the range of operating conditions is relatively small and no nonlinear chemical reactions are involved. This fact suggests the use of simple linear models (step or impulse response model). For the paper plants considered in the present study, it was found that the impulse model with the order of 17 fits the plant data very well compared to other types of models.

A multivariable impulse model can be expressed by

$$y_k(t)=\sum_{j=1}^{nu}\sum_{i=1}^{n} b_{k,j,i}u_j(t-i) \quad (k=1,\dots,ny) \qquad [2]$$

nu : input number

ny : ouput number

$b_{k,j,i}$: impulse parameter element.

The ARX formulation of the impulse model is given by

$$A_0Y(t)=B_1U(t-1)+B_2U(t-2)+\mathrm{L}\ +B_nU(t-n)$$
$$A_0=[100;010;001]$$
$$B_i=\begin{bmatrix} b_{1,1,i} & b_{1,2,i} & b_{1,3,i} & b_{1,4,i} \\ b_{2,1,i} & b_{2,2,i} & b_{2,3,i} & b_{2,4,i} \\ b_{3,1,i} & b_{3,2,i} & b_{3,3,i} & b_{3,4,i} \end{bmatrix}$$
$$U(t-i)=[u_{speed}(t-i)\ u_{stock}(t-i)\ u_{filler}(t-i)\ u_{steam}(t-i)\ ]' \qquad [3]$$

A_0 : unit matrix

B_i : impulse parameter matrix

$b_{i,j,k}$: impulse parameter element in B_i matrix

u_{speed} : speed, m/min

u_{stock} : thick stock, L/min, m^3/min

u_{filler} : filler flow, L/min

u_{steam} : steam pressure, kg/cm^2.

Matrices B_i contain impulse model parameters to be identified. A simple least-squares curve fitting method available from various computational tools such as MATLAB can be used in the identification. Figs. 5 and 6 show the results of validations of the impulse model for the paper company A and B respectively. As we can see in Figs. 5 and 6, the impulse model tracks the plant confidently.

Predictions of outputs can be represented as

$$\hat{y}_k(t+l\,|\,t)=\sum_{j=1}^{nu}\sum_{i=1}^{n} b_{k,j,i}U_j(t+l-i)+\hat{n}_k(t+l\,|\,t) \quad (k=1,\dots,ny)$$
$$(j=1,\dots,nu) \qquad [4]$$

$$\hat{y}_k(t+l|t)=\sum_{j=1}^{nu}\sum_{i=1}^{l} b_{k,j,i}U_j(t+l-i)+\sum_{j=1}^{nu}\sum_{i=l+1}^{n} b_{k,j,i}U_j(t+l-i)+\hat{n}_k(t+l|t) \quad (k=1,\dots,ny) \qquad [5]$$

$\hat{y}_k$: predictive output

$\hat{n}_k$: noise.

If the future noise is assumed to be kept as the present noise, we have

$$\hat{n}_k(t+l\,|\,t)=\hat{n}_k(t\,|\,t)=y_k(t)-\sum_{j=1}^{nu}\sum_{i=1}^{n}b_{k,j,i}U_j(t-i)\quad (k=1,\dots,ny) \qquad [6]$$

y_k : measured output.

At first, we assumed that the measured output $y_k(t)$ is equal to the value computed from the model, $\sum_{j=1}^{nu}\sum_{i=1}^{n} b_{k,j,i}U_j(t-i)$. The desired output trajectory can be defined as

$$\omega_k(t+l)=\alpha\cdot\omega_k(t+l-1)+(1-\alpha)\cdot\gamma(t+l) \qquad [7]$$

w : desired output trajectory

α : parameter in desired output trajectory

γ : setpoint.

The predicted outputs can be written as

$$Y=H_{pl}U_{pl}+H_{mi}U_{mi}+n=H_{pl}U_{pl}+f \qquad [8]$$

H_{pl}, H_{mi} : dynamic matrix

U_{pl} : future input

U_{mi} : past input.

The combination of a linear model and a quadratic objective function lead to an analytical solution for the control moves as given by

$$U_{pl}=(H_{pl}{}^{T}H_{pl}\cdot Q+\lambda\cdot I)^{-1}\cdot H_{pl}{}^{T}\cdot(\omega-f) \qquad [9]$$

In practice, constraints on manipulated inputs can be very important. If the analytical solution results in an infeasible control action, then obviously the control moves must be truncated at the maximum or minimum values. Since the resulting truncated solutions may not be optimal if the control horizon is greater than 1, it is important to use a constrained optimization formulation for these problems. Fortunately,

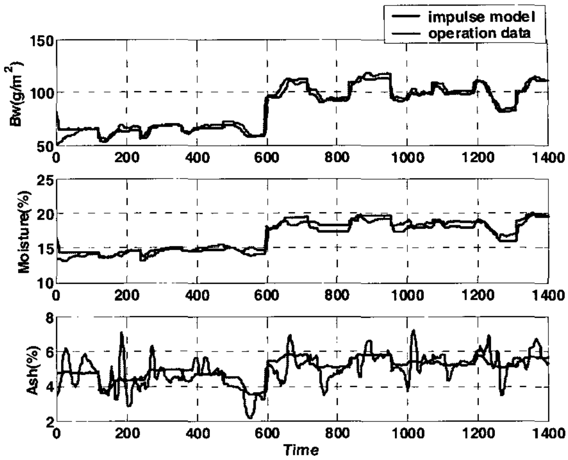

Fig. 5. Validation of the impulse model (Company A).

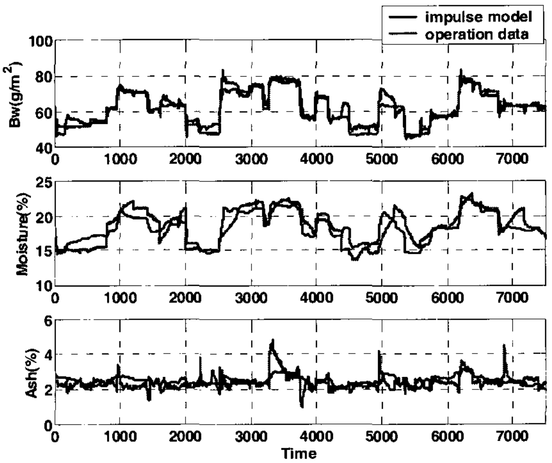

Fig. 6. Validation of the impulse model (Company B).

MAC is easily formulated to explicitly handle constraints by using quadratic programming.

5. Results and Discussion

In steady-state operation, an appropriate control method can be used to stabilize process operations and especially to stabilize the short circulation. This will mean stable retentions. However, the control task is very different during grade change operations. The primary objective is to minimize the grade change time. This leads also to short control horizon and larger allowed control actions, because before a grade change time MAC should already be running the process towards a new grade. Yet, as well, it is necessary to keep product quality at accepted grade specifications as long as the old grade run is continuing. Prevention of web break is by far the most important target during the grade change operation. At the end of the grade change, the process should meet the limits of the new grade as soon as possible and not overshoot outside quality limits. But, in actual operations, overshoot less than $\pm 5\%$ of the grade change span is usually allowed. The optimization horizon and the number of actions in the calculated sequence must be extended towards the end of the grade change.

In most grade change operations, changes of concurrent machine speed are also included. Moisture content is usually a challenging variable for automatic grade changes. Water content after the press section would be dependent upon many variables including machine speed, paper basis weight and ash content. The paper web inside drying section during grade change will have special conditions. There will be different basis weight in each drying section. Also a piece of paper web will have different speed in each drying section compared to pieces in other drying sections. If we increase the web speed, we will decrease drying time in the drying section at the same time. This fact implies that we must increase drying power correspondingly. The drying process itself is also dependent upon heat production at the heated drying cylinders and water evaporation conditions in the hood.

In the beginning of each grade change it is important to have a good predictive model to adjust manipulated variables, almost according to traditional open-loop grade change program. At the end of grade change, we must smoothly move towards steady-state MAC operation by extending the prediction horizon and decreasing the amount of control movement allowed during each optimization cycle. The performance of the proposed control scheme was evaluated by using numerical simulations. Grade change operation data were collected for the plant A and plant B. For the plant A, the prediction horizon was set to 16 and the input suppression parameter was set to 17. After some trials, the suitable weights for the outputs (Qo) and the inputs (R) were found to be [3 1 1] and [0.1 0.1 0.2 0.1] respectively. The parameter in the desired output trajectory (α) was set to 0.85. For the plant B, the same values as for the plant A were used for the prediction horizon and the input suppression parameter. The suitable weights for the outputs (Qo) and the inputs (R) were found to be [3 3 1] and [0.1 0.1 0.2 0.1] respectively. The parameter in the desired output trajectory (α) was set to 0.9. The sampling time was 30 sec (0.5 min).

Figs. 7 and 8 show results of numerical simulations for the grade change of 110→84 (g/m^2) in the plant A. It is normal practice to express a grade change operation in terms of the basis weight (BW) because BW is the most important output variable. Fig. 7 shows the optimal input trend obtained from MAC compared to the plant operation data. We cannot say which one is "better", but the primary concern is to avoid unnecessary oscillations or perturbations in the inputs. Fig. 8 shows the output trend. In Fig. 8, the MAC line was obtained by applying the optimal inputs from MAC to the "plant". As described before, the "plant" is the neural network model

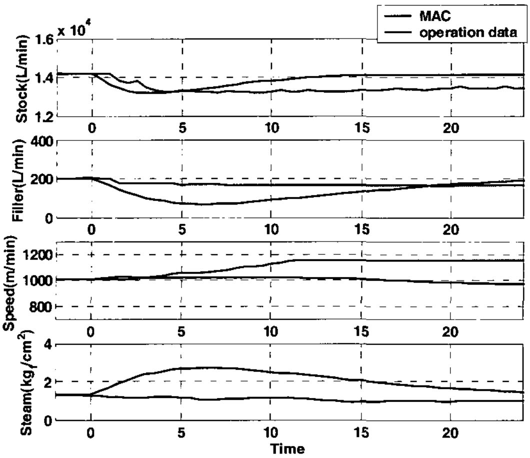

Fig. 7. Input trend for 110 g/m^2→ 84 g/m^2 (Company A).

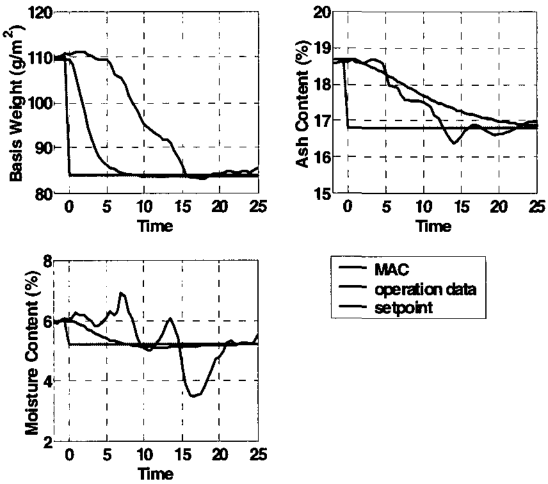

Fig. 8. Output trend for 110 g/m^2 → 84 g/m^2 (Company A).

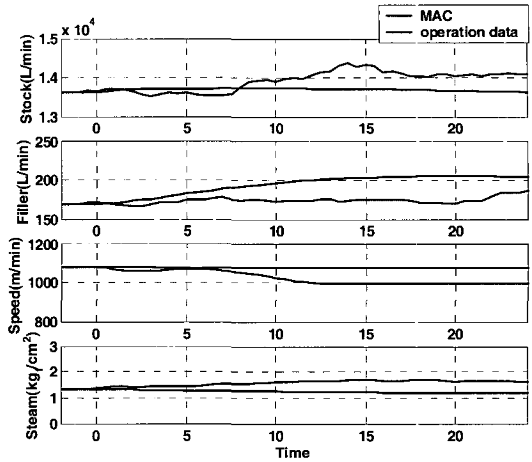

Fig. 9. Input trend for 96 g/m^2 → 110 g/m^2 (Company A).

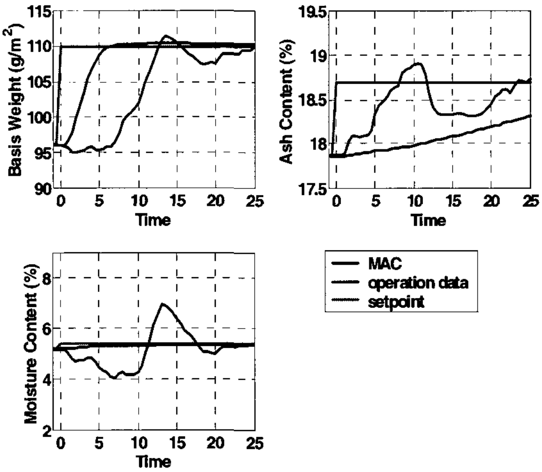

Fig. 10. Output trend for 96 g/m^2 → 110g/m^2 (Company A).

for the plant and the accuracy of the neural model was depicted in Figs. 3 and 4. It is obvious that the grade change time was reduced up to 50% (approximately from 15 min. to 7 min.) and that oscillations were suppressed enough. This fact makes the application of MAC scheme in the plant operation promising. Figs. 9 and 10 show similar results for the grade change of 96 →110 (g/m^2) in the plant A. Again the grade change time was reduced more than 50 % and the trends obtained by MAC show smooth behavior without overshoots.

Figs. 11 and 12 show results of numerical simulations for the grade change of 57.5→73 (g/m^2) in the plant B.As in the case of plant A, we can see that decrease in the grade change time and smooth trends are successfully achieved by MAC. Figs. 13 and 14 show similar results for the grade change of 47.5→57 (g/m^2)

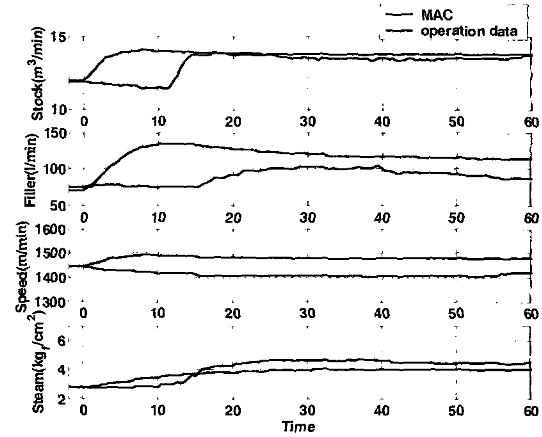

Fig. 11. Input trend at 57.5 g/m^2 → 73 g/m^2 (Company B).

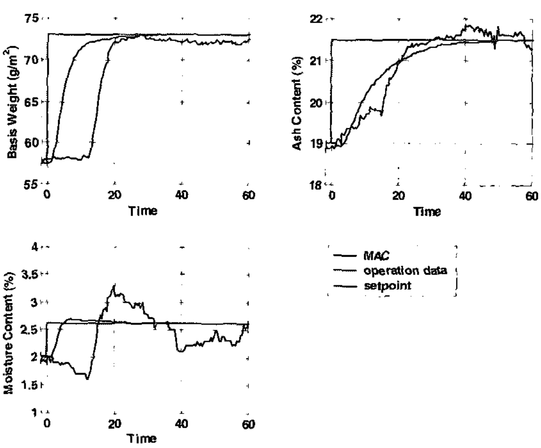

Fig. 12. Output trend at 57.5 g/m^2 → 73 g/m^2 (Company B).

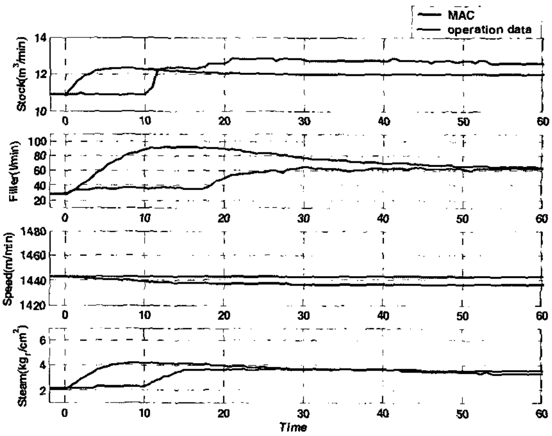

Fig. 13. Input trend for 47.5 g/m^2 → 57 g/m^2 (Company B).

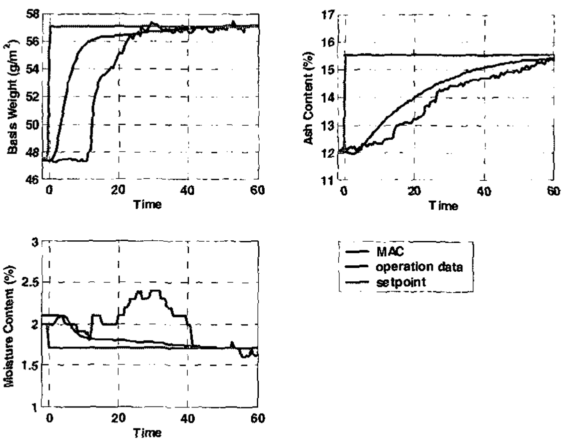

Fig. 14. Output trend for 47.5 g/m^2 → 57 g/m^2 (Company B).

in the plant B. Again the grade change time was greatly reduced and the trends obtained by MAC show smooth behavior without perturbations.

6. Conclusions

The most challenging issue for the automatic grade change operation is the reduction of grade change time without web break. This leads to short control horizon and larger allowed control actions, because before a grade change time the model predictive control method being used should already be running the process towards a new grade. The Model Algorithmic Control scheme based on the impulse plant model was found to achieve the expected primary control objectives: reduction in the grade change time and suppression of input/output trends. The neural network model for the grade change operations were developed first. From the numerical simulations the neural network model was found to track the plants exactly. Thus the neural model acted as the real plant in the control simulations. The MAC proposed in the present study showed desired performance: the grade change time was decreased more than 50 % and the input/output trends showed smooth behavior without severe oscillations.

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